Pairing Bayesian Methods and Systems Theory to Enable Test and Evaluation of Learning-Based Systems

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■ **ABSTRACT**
Modern engineered systems, and learning-based systems, in particular, provide unprecedented complexity that requires advancement in our methods to achieve confidence in mission success through test and evaluation (T&E). We define learning-based systems as engineered systems that incorporate a learning algorithm (artificial intelligence) component of the overall system. A part of the unparalleled complexity is the rate at which learning-based systems change over traditional engineered systems. Where traditional systems are expected to steadily decline (change) in performance due to time (aging), learning-based systems undergo a constant change which must be better understood to achieve high confidence in mission success. To this end, we propose pairing Bayesian methods with systems theory to quantify changes in operational conditions, changes in adversarial actions, resultant changes in the learning-based system structure, and resultant confidence measures in mission success. We provide insights, in this article, into our overall goal and progress toward developing a framework for evaluation through an understanding of equivalence of testing.
■ **KEYWORDS:** Test and Evaluation; systems theory; Bayesian; Learning; artificial intelligence

INTRODUCTION

Test and evaluation (T&E) frameworks for learning-based systems (LBS) are currently in their nascent stage, with existing frameworks lacking specificity and needing to be piloted against actual LBS. By the term LBS, we refer to an array of systems, based on artificial intelligence (AI), with adaptive learning behavior stemming from training data, such as machine learning (ML) computer vision algorithms. A particular challenge arises when considering the impacts of changes in operational conditions and adversarial actions, which may notably vary over the life-cycle of an LBS and cause deviation of the LBS from design limits (Lanus 2021). Traditional systems employ a black-box T&E method of providing sampled inputs, from which outputs are measured against expectations. LBS's complexity and dynamics suggest challenges in applying traditional methods (Freeman 2020).

This paper reports on the status of a Systems Engineering Research Center (SERC) project that aims to establish theory and methods for how T&E requirements can and should change as a function of the test team's knowledge of LBS technical specifications. An overarching objective of this research is to characterize the balance between the design of T&E activities and the cost of data/model rights acquisition for LBS. This informs government decision-makers on the emerging necessity for a new policy. We focus this research article on building from past research on a notional networked munition system of systems for ground denial, referred to as the Silverfish Testbed (Carter 2019), which we leverage to provide insights to our initial T&E framework for LBS.

We develop a framework consisting of Bayesian methods and a system theoretic basis for the mathematical characterization of equivalence between pairs, referred to as a morphism. The project experimented with two pilot scenarios to demonstrate how multiple testing phases contribute to evaluating an LBS, using morphisms as guiding principles. The pilot scenarios center on an unmanned aerial vehicle (UAV), providing vehicle and human detection functions in the Silverfish notional weapons system. These detection functions use the You Only Look Once (YOLO) image recognition agent (Redmon 2016) trained on the Common Object in Context (COCO) data set of images (Lin 2014) and paired with simulations and real drones. From knowledge of morphic equivalence, we frame the correlation between scenarios and resulting confidence in mission success through Bayesian methods.

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We share insights from our initial framework, practical development, and expected future activities in the following sections.

GOALS AND OBJECTIVES

The complexity of T&E for LBS is unparalleled when compared to traditional systems. LBS have a rate of evolution based on behavior changes due to the data ingestion rate, which generally has a high frequency, such as in the measure of fractions of a second. Traditional systems, alternatively, are expected to have a low frequency of behavior change, even with changes in input. Furthermore, traditional systems may typically be viewed as deterministic, whereas LBS are viewed from a probabilistic context. Such distinctions between traditional systems and LBS suggest that new T&E methods are necessary to cope with the magnitude of complexity.

Further complexity arises from the necessity to rely on surrogate analogies to achieve confidence in mission success during developmental testing (DT) of LBS. First, the environments and operational conditions of the mission are often analogies to the full scope of the mission set. For example, a system developed for a mission to Mars would leverage a surrogate analogy to the Mars environments on Earth (such as desert climate) to gain confidence in mission success before deployment to the actual Mars environment. Second, the real system may not be available during DT; surrogate analogous systems are used instead. For example, in our case, we use simulation and a low-cost drone as surrogate analogies for the UAV "real" (fielded) system.

This research is driven toward developing a T&E framework for LBS through the necessity to understand the equivalence between and confidence from using the surrogate analogies versus the fielded system and actual mission. An overarching goal of this research is to reach the characterization of the tradespace between the design of T&E activities and the cost of changes in policy to acquire increased access to data/model rights for LBS. To understand this tradespace, subsequent objectives are defined as follows:

- Characterize the change in operational conditions and adversarial actions;
- Characterize the impact of change in operational conditions and adversarial actions on changes to the system implementation and behavior; and
- Create a T&E framework for LBS that characterizes the balance between T&E activities and data/model rights acquisition costs.

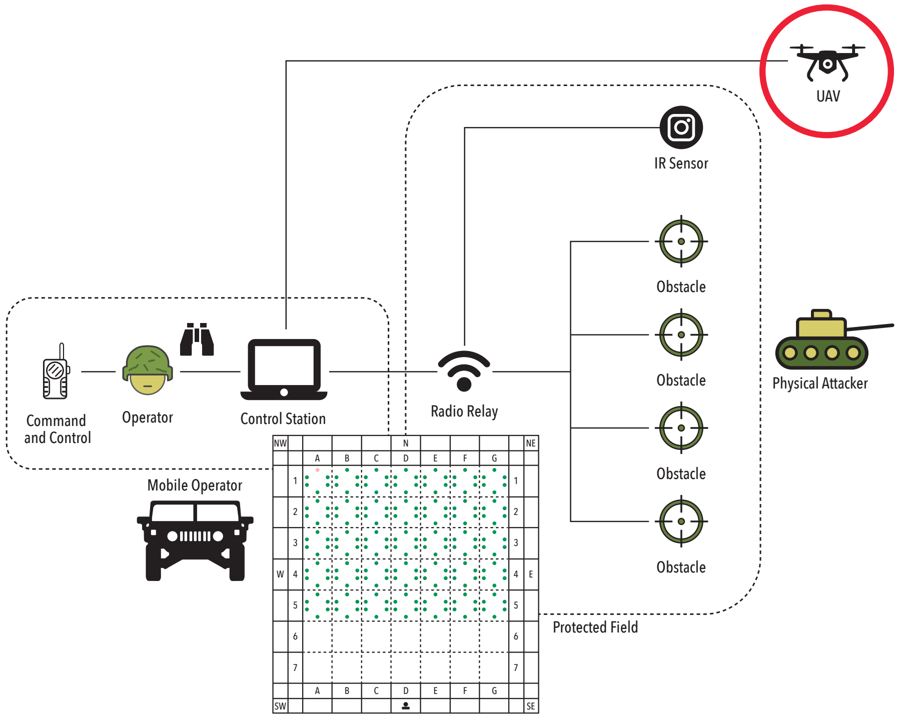

Figure 1. The UAV within Silverfish's notional system of systems context is considered to be the system of interest for this research article

This article provides insights into the creation of the T&E framework. We discuss the framework (1) in terms of notional use for the characterization of changes in operational conditions and adversarial actions, which we refer to as a systems theoretic morphism between the mission and mission surrogates used for T&E; (2) in terms of notional use for the characterization of changes in system implementation and behavior, which we refer to as a systems theoretic morphism between the fielded system and surrogate systems used for T&E; and (3) in terms of notional decision context. The characterization of the balance between T&E activities and data/model rights acquisition cost is left for future research. However, we provide insights into the Bayesian methods that are in development and, when paired with systems theory, will be used to reach the overarching goal.

TESTBED ENVIRONMENTS

The primary testbed for this research is a notional weapons system of systems named Silverfish. Silverfish is used to deny ground to adversaries through a networked munition system with integrated surveillance and situational awareness technology. The system of systems includes the protected area, a UAV that performs surveillance functions, tripwire and infrared ground sensors, and a human operator in charge of command and control. Data from the UAV cameras and the ground sensors are fused to provide situational awareness of the protected area, emphasizing the detection of humans or vehicles. In the event of a detection, the operator is provided with a likelihood that the entity traversing the protected area is a combatant versus a non-combatant. The human is responsible for final decisions, including engaging a target with the networked munitions. We provide the Silverfish notional system in Figure 1 to illustrate the system of systems.

The Silverfish testbed continues to expand from its conception. In the original implementation, Silverfish included a network of connected Raspberry Pi ® to emulate the protected area and ordinance. In line with digital engineering (DE), a model-based systems engineering (MBSE) implementation of Silverfish was defined in the GENESYS tool (Long 2019). More recent progress by our research group has included some initial transition of the MBSE implementation to the Cameo MBSE tool (NoMagic), simulation, and physical testing through the pairing of the YOLO algorithm with UAV/drone hardware.

In this article, our current focus is on the UAV element of Silverfish and T&E for its LBS nature. We refer to the LBS element of the UAV as Agent YOLO, for the name of the computer vision algorithm leveraged therein. The YOLO algorithm provides an open-sourced algorithm to fulfill the intent of a cascade of analogies with respect to the development sequence. The cascade includes T&E surrogates of the Silverfish

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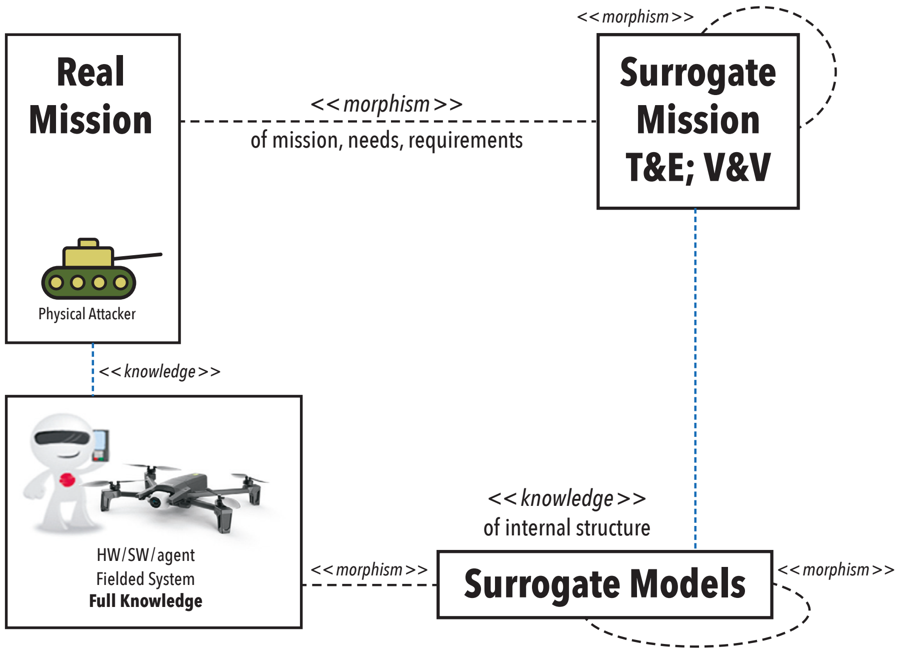

Figure 2. Proposed systems theoretic test and evaluation framework

UAV and surrogates of its mission context within the Silverfish system of systems, which is to surveil a protected area, identify potential attackers, and report the surveillance activities to the human command and control element.

OVERVIEW OF FRAMEWORK

Our framework consists of two parts: (1) systems theoretic characterization of stratification as well as characterization of equivalence referred to as system morphisms and (2) Bayesian method characterization of correlation in confidence in mission success.

We provide a visualization of the systems theoretic aspects of the framework in Figure 2, which builds on the research found in Wach 2021; Wach 2022a; Wach 2022b). The horizontal lines reflect morphic equivalence between surrogate analogies with the real mission and the fielded system; the vertical lines reflect knowledge of the interior structure of the LBS system implementation. Each surrogate may have morphisms relative to other surrogates (mission-mission and model-model). There is a corresponding cost associated with acquiring the data for systems. To account for the many levels of data-driven knowledge, we use systems theory to mathematically characterize the iterative and recursive stratification.

We provide a visualization of the Bayesian aspect of the framework in Figure 3. We use a Bayesian network to characterize the probability of outcomes across the testing phases; the network's edges represent conditional probabilities that can be used to compute the probability of—or the operational cost associated with—outcomes at each layer. In this simple example, we use three layers to represent three different system types that might be evaluated, including in the Silverfish context, System 1 might be a pairing of Agent Yolo with prototype hardware for a developmental test activity, System 2 might be a pairing of Agent Yolo with low-rate initial production hardware (LRIP) in an initial operational T&E (IOT&E) activity, and System 3 might be the real mission and fielded system. We then categorize the outcomes from those systems into two cases, Case A and Case ¬A ("not A"), which might, for example, correspond to "detect" and "no detect" in the context of Silverfish. We elaborate further in the next section; see Figure 5 in particular.

The Bayesian network is paired with the cascade of knowledge of the results of T&E activities, which builds on the research found in Salado (2018). This knowledge includes the systems theoretic characterization of morphic equivalence and internal structure. The combined and framed knowledge impacts overall confidence in mission success from the deployment of the LBS, which can be paired with utility metrics such as cost/schedule for predictive capabilities. In doing so, the framework enables the characterization of the relationship between the design of the evaluation activities and the characterization of equivalence. When we pair the systems theoretic morphisms with Bayesian methods, we have a fabric for connecting information and determining T&E priority. For example, we may select a cheap drone for a T&E activity as a surrogate or a more expensive drone because we believe the drone to have a low probability of mission degradation when considering the overall LBS. Thus, an impact of the framework is the ability to narrow down cases that are most likely to fail or cause problems. By connecting levels of knowledge of the surrogate analogies to confidence, we can weigh the cost of a T&E activities in light of their importance to mission success.

INITIAL RESULTS

In this section, we provide insights into the results. We focus here on a T&E activity consisting of detecting automobiles and using physical drones paired with Agent YOLO, which have various morphic equivalence to the real mission and fielded system. We have a cheap prototype drone paired with Agent YOLO in the first case. In the second case, we have the higher-cost LRIP drone paired with Agent YOLO. Both drone/agent pairs were simultaneously tested and evaluated for detecting automobiles, which is a surrogate mission scenario for detecting a potential attacker. A visualization is shown in Figure 4.

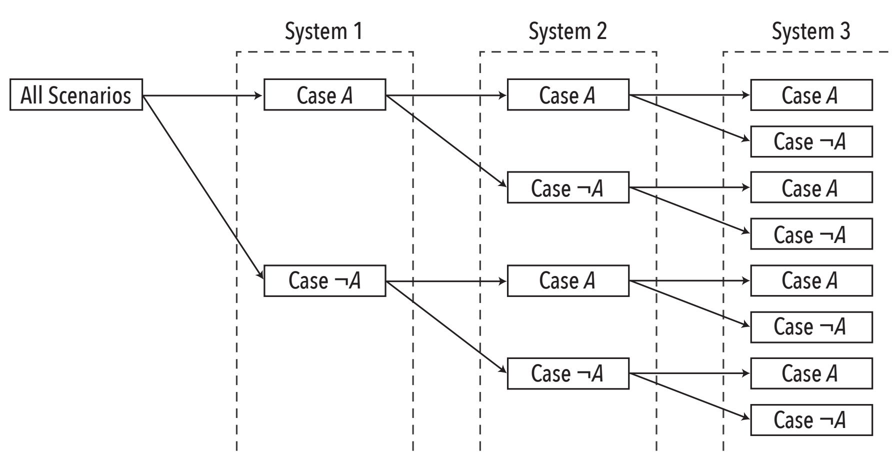

Figure 3. A visualization of the Bayesian aspect of the framework

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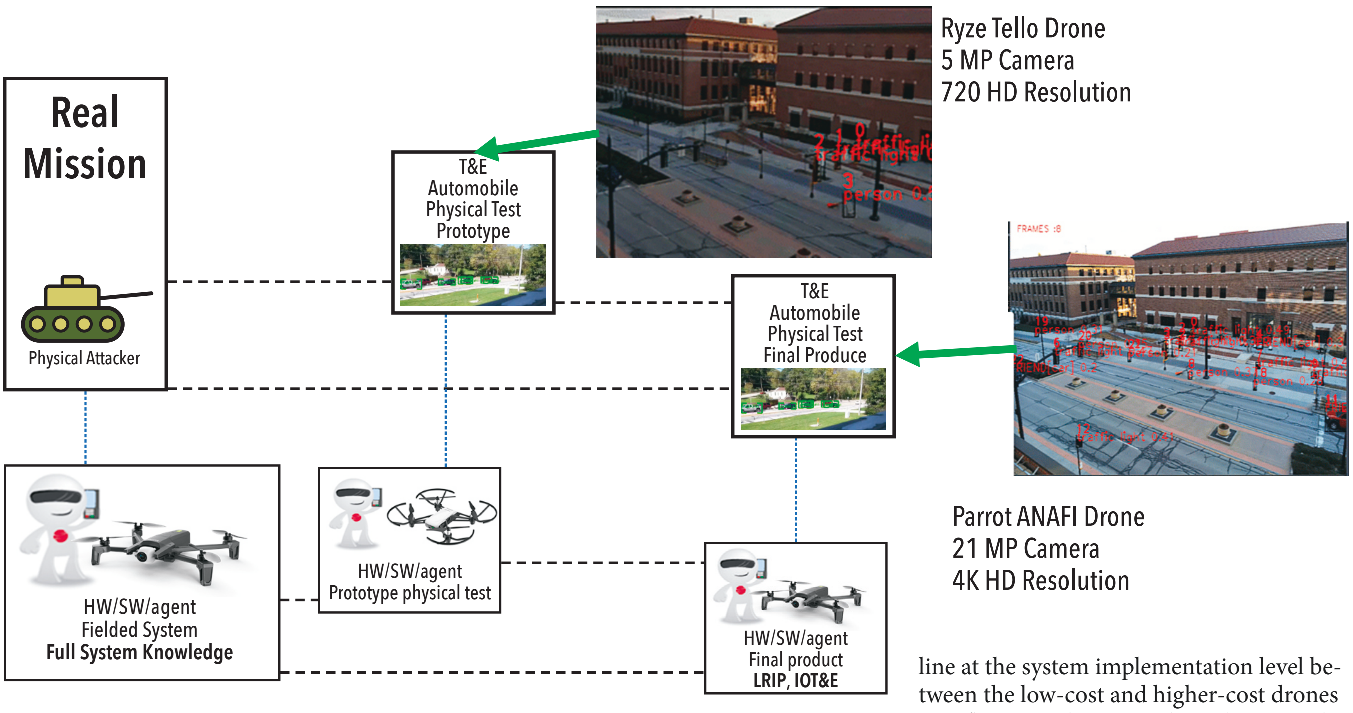

Figure 4. A visualization of the systems theoretic framing of the test context

To further elaborate on the two drones used for this study: The first drone used is a lower-cost drone (Ryze Tello), which has cost-corresponding attributes such as camera megapixels (5 MP) and resolution (720 HD). The second drone used is a higher-cost drone (Parrot ANAFI), which has cost-corresponding attributes such as camera megapixels (21 MP) and resolution (4k HD).

Each drone served as a representation of a phase of system development with the corresponding testing. We treat the low-cost drone as a prototype that may be used in the early development of a system for a developmental test. We treat the higher-cost drone as resembling what may be produced during LRIP for IOT&E.

We used simultaneous testing of the drones, although one would typically expect time to elapse between tests following phased system development. Each drone was positioned side-by-side at the same time of day and in view of the same street. During the test activity, Agent YOLO, paired with each drone, characterized the vehicles as they passed on the street.

The vertical lines in Figure 4 reflect morphic equivalence at each system specification level, similar to Figure 2. In this case, we add a vertical line at the mission level of system specification between the test conducted on the low-cost drone and the test conducted on the higher-cost drone to reflect morphic equivalence between the tests. Also, in this case, we add a vertical line at the system implementation level between the low-cost and higher-cost drones to reflect morphic equivalence between the drones.

The knowledge of morphic equivalence may be complemented by a confidence factor defined by Bayesian methods, as shown in Figure 5.

The images of the street and vehicles passing by are shown in Figure 4 at the top middle for the lower-cost drone and to the right side for the higher-cost drone, which is unaltered and can be observed to have visual differences. Although there is nearly an exact morphic equivalence at the mission level, there is a lower degree of morphic equivalence at the drone system implementation level. The morphisms provide knowledge to frame the overall equivalence, which feeds into confidence in mission success. Using Bayesian methods, the success (or lack thereof) detection and

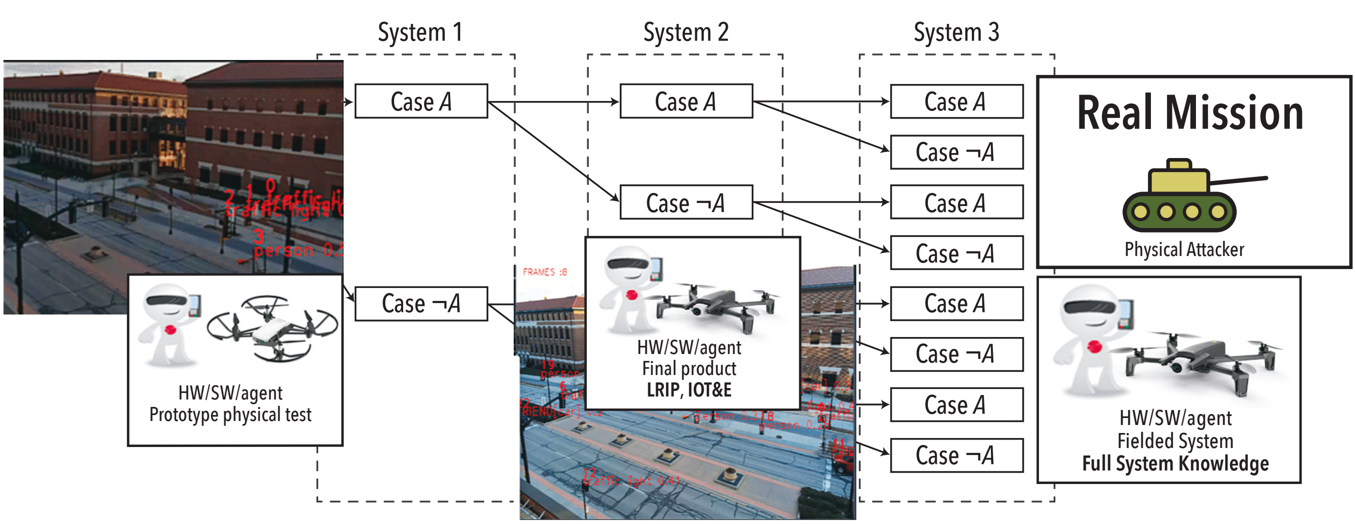

Figure 5. A visualization of the Bayesian propagation of confidence

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categorization of the automobiles with the lower-cost drone indicate success for the higher-cost drone. The complementary pairing of system morphisms with Bayesian methods provides the basis for our framework for the T&E of LBS.

FUTURE WORK

Our future efforts are threefold: (1) link the LBS lifecycle, (2) advance the digital engineering aspects, and (3) prove the value to the government.

As discussed in this article, we have focused our initial efforts on the DT aspects of T&E. Our future efforts will continue from DT to later aspects of the LBS lifecycle. We plan to show the propagation of knowledge and confidence in mission success from the DT to the operational, surveillance, and maintenance phases of the LBS lifecycle. Furthermore, knowledge of retirement and legacy systems propagates perceived confidence in new systems, which we will explore in future work.

We are exploring several paths to advance the digital engineering aspects of the framework. One, we are exploring creating plugins for the Cameo MBSE tool and constructs based on the Systems Modeling Language (SysML). We plan to enhance the framework through digital twin and physical twin pairing. We are also exploring creating an expert system to advise the human decision-maker (s) during acquisition and deployment based on the T&E framework. Lastly, we anticipate linking the framework to a "born-digital" Test and Evaluation Master Plan (d-TEMP). These are some of the digitally enhanced efforts either in planning or in progress.

To reach the main goal of this effort, we desire to prove the value to the government and use the framework to assess the tradespace between confidence in mission success and resources necessary for acquiring increased data/model rights to LBS. First, we plan to add utility metrics to the Bayesian methods and simulate policy changes to accomplish this. Second, our data set is currently small, and we would like to expand it with more control. As an example, we are proposing using a controlled group of students traversing a field to emulate the red/blue scenario. Furthermore, we are leveraging commercial-off-the-shelf drones with limited insights and control over their hardware and software, increasing our urgency to create our controlled hardware/software. Last, we plan to up-scale the framework from the controlled development environments to real LBS acquisition, deployment, and policy decision-making.

CONCLUSION

We present a novel framework for the T&E of LBS. The framework consists of a systems theoretic basis for determining equivalence from surrogate analogies used for T&E relative to the real mission and system implementation. The framework uses Bayesian methods to characterize confidence in mission success. We initially framed LBS through simulation and physical testing, which has shown promise. This article is focused on exposure to the framework rather than the data and specifics of the mathematical basis. Finally, we discuss aspirations for the T&E framework for LBS. ■

DISCLAIMER

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